Public investments in ICTs and learning performance. Evidence from Italy

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Abstract

In this paper we provide a detailed and robust estimation of the impact of three different digital technologies (IWBs, wireless connections and mobile devices) on Italian language and mathematics performance in lower secondary schools in Italy. Our dataset offers longitudinal data in three different school years in the 2010-2014 period for the lower secondary school universe in Italy. The results show that no significant effects emerge at a national level from the increase in any of the three technologies considered, confirming the literature. However, when controlling for geographical area, data show that all three technologies have exerted positive effects on mathematics results in the North of Italy, while on the contrary there has been a detrimental effect in the South. Further analyses show that the positive effect found in the North is driven by low-attaining schools, while the negative impact emerging for the South is driven by higher attaining schools. No effects were found on Italian language performance, except for a slightly positive impact in the lowest-achieving schools in all geographical areas. In the conclusion, the significance of these results is discussed with regards to future public intervention and research in this field.

1. Introduction

In the last two decades, an unprecedented amount of money has been invested worldwide in communication technology for schools. In Europe, the introduction of information and communication technology is a goal under the EU2020 strategy and the Digital Agenda for Europe (as it was in the previous Lisbon strategy). The official European documents clearly indicate the improvement of students' learning outcome as the main goal expected from this kind of investment (Giusti et al., 2015). A similar expectation of learning enhancement and improvement in student achievements seems to have informed US education policies (U.S.

Department of Education 1996; 2000). Moreover, an implicit agreement appears to exist between parents, teachers and learning institutions that technology can serve as a teaching aid, and that it can raise learning achievement (Selwyn, 2012; Selwyn and Cooper, 2015; Buckingham, 2013). This hope has helped to fuel the rapid diffusion of ICT in schools.

As a consequence of these expectations, the technology stock in Europe has grown steadily and swiftly: in the 2011-12 school year the number of computers per 100 students almost doubled compared with 2006, and the percentage of schools with a website, email addresses for teachers and students and a local area network is rapidly increasing (European Schoolnet, 2013). In most countries, digital equipment and facilities have taken precedence on digital training for teachers, in particular with the purchase of Interactive Whiteboards (IWB), laptops and tablet computers (Eurydice, 2011). In Italy, the country on which this paper focuses, the Ministry of Education invested €127 million euros in the 2007-2012 period through the 'Piano Scuola Digitale', €89 million of which was dedicated to the purchase of digital equipment, for the most part IWBs (MIUR, 2015). Moreover, four Italian regions (the so called 'convergence regions'[1]) eligible for funding from the European Structural Funds under the convergence objective for the 2007-2013 period (Campania, Calabria, Puglia and Sicily) received an additional €494 million for the purchase of digital equipment (MIUR, 2015). Recently, the new government plan for digital technology in Schools (MIUR, 2015) has allocated €1.94 billion in new investments, covered by both national and European funds, of which at least €511 million is for hardware and software technology.

These massive investments have been made despite the fact that so far there has been no agreement between scholars on the impact of ICT investments on standardised learning performances. Indeed, in contrast with solid evidence of positive effects found in randomised controlled trials (Tamim et al., 2011), field research has mainly found less comforting results (Barrera-Osorio & Linden, 2009; Cristia et al., 2012; Campione et al., 2015). A recent report by the OECD based on PISA 2012 data (OECD, 2015) has cast additional doubts on the positive impact of technology on school learning, showing that most countries that have invested heavily in digital equipment have not shown signs of appreciable improvements in student achievement over the past ten years. However, so far no studies have analysed the relationship between the device-specific technology stock present in schools and learning performance. Furthermore, we

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[1] Convergence regions are defined as those regions having a per capita gross domestic product (GDP) lower than 75% of the average GDP of the EU-25 (Commission Decision C(2006)3475 of 4th August 2006 and Commission Decision C(2007) 1283 of 26 March 2007 amending European Commission's Decision 2006/595/EC as concerns Bulgaria and Romania).

do not know whether the impact of these devices on learning outcomes differs according to the socio-economic context of the areas in which schools are located. Finally, in most cases studies have not been able to check for unobserved heterogeneity in schools in their estimates. These constitute significant gaps in literature.

In this paper we use institutional panel data to estimate the impact of increases in schools' technology stock on average learning achievements in lower secondary schools in Italy, in the 2010-2014 period. The dataset used was built by merging data from the Technology Observatory of the Italian Ministry of Education with data from SNV/INVALSI (the national school learning performance survey) standardised tests (in Mathematics and Italian language) administered to students during the lower secondary school final exams in the years 2010-11, 2011-12 and 2013-14.[2] Thanks to the unique richness of the dataset, we can test the specific impact of three technologies, which have been massively introduced in the period considered: interactive whiteboards, wi-fi connection in classrooms and mobile devices. Furthermore, we explore the differential impact these technologies have had on student performance in different areas of the country with different socio-economic situations: the north, the centre and the south[3], with the latter having received massive injections of European funding for the purchase of technology in the period considered.

As far as we know, this is the first study making use of institutional panel data on schools' technology equipment at a national level in order to answer questions about the impact of specific digital devices on school performance in different areas of the country.

2. Literature Review

The literature about the relationship between ICTs and school learning outcomes is mixed in its conclusions.

A simple distinction can be made between experimental studies and field studies, where the former measure the impact of specific didactic technologies in controlled trials and the latter usually assess the effects of public policies aimed at integrating ICT in schools. Regarding the former, several meta-analyses on decades of experimental research exist: Bangert-Drowns, 1993 examines the impact of word processors at different grade levels; Cohen and Dacanay (1992) consider computer-based instruction at post-secondary level, Christmann and Badgett

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[2] In the 2012-13 year the Technology Observatory of the Italian Ministry of Education did not carry out its annual survey.

[3] The north includes Liguria, Piedmont, Lombardy, Veneto, Friuli Venezia Giulia and Emilia Romagna; The centre includes Tuscany, Marche, Umbria and Lazio; finally, the south includes Abruzzo, Molise, Campania, Basilicata, Apulia, Calabria, Sicily and Sardinia.

(2000) computer-aided teaching in high school; Bayraktar, (2001) computer-aided teaching in science among K–12 students. All these studies find positive average effects.The more recent meta-analysis by Timmerman and Kruepke (2009) summarises the results of 57 papers comparing the effect of computer-aided teaching with traditional educational formats on students' achievement in higher education also finding a statistically significant positive average effect. A second-order meta-analysis of 25 meta-analyses considering forty years of studies (Tamim et al., 2011) confirms the robustness of these findings. Even if we focus solely on studies that look at the use of digital media in middle school, which is the object of this study, we find similar outcomes (Moran et al., 2008; Tienken and Wilson, 2007). However, the problem with these experimental studies is that they measure the effect of specific uses of ICT, often based on specific software and pedagogical approaches. Therefore, one could wonder if the effect found should be attributed to the technological environment or to the learning approach used, or to a mix of both. For example, Liu et al. (2004), authors of the study with the highest effect found in the meta-analysis of Moran et al. (2008), measure the effect of a problem-based hypermedia learning environment (*Alien Rescue*) among a group of sixth-graders. More in general, the presence of specific learning approaches and ad-hoc software can be found in the majority of the studies that show high positive effects (see Salomon et al., 1989; Higgings & Raskind, 2005; Barrow et al., 2009 as illustrative examples).

Different results have emerged when scholars have investigated the impact of a simple and undifferentiated provision of technology to schools (or families), as often happens in public ICT equipment investment policies. A number of studies have attempted to provide causal estimates by exploiting the exogeneity of public programmes aimed at providing more ICT equipment in schools and have found either little or no effect in many countries (Barrera-Osorio and Linden 2009 on Colombia; Cristia et al. 2012 on Peru). Higgins et al. (2005) have evaluated the 'Embedding ICT in the Literacy and Numeracy Strategies' pilot project, which involved the installation of interactive whiteboards (IWBs) in Year 5 and Year 6 classes in 12-15 schools in six separate Local Education Authorities (LEAs). In terms of impact on pupils' attainment, the IWBs appeared to have a negligible effect. However, the analyses also show that the proportion of low-attaining pupils in the IWB group decreases, and this constitutes evidence that the use of IWBs improves the performance of low-achieving pupils in English. Moss et al. (2007) have evaluated the effects of the Secondary Whiteboard Expansion (SWE) project, which expanded the use of IWBs into secondary schools in the UK. Statistical analysis showed no impact on pupil performance in the first year in which departments were fully conversant with the new technology. Heemskerk et al. (2014) compared different classes of a single school which had

or had not been taught with an IWB throughout a period of 3 years and found no relation between the frequency of this practice and performance in mathematics. The Italian counterfactual study of Checchi et al. (2015) shows that the project Cl@ssi 2.0 (resources allocated for purchasing ICT school equipment in the 6th grade) did not produce a significant increase in student achievement, but they confirmed a slightly positive effect for those with the lowest socio-economic backgrounds only. Some exceptions are also present in this literature. The study by Hyland et al. (2015) finds that the presence of broadband access in class is associated with significantly higher average mathematics and reading scores among 9-year-olds in Ireland. Others studies show mixed findings: Machin et al. (2007) investigated the impact of a change in the way ICT funding is assigned across different school districts in England and find a positive impact in English and science but not for mathematics among primary school students' performance. The most comprehensive results about the relationship between ICT diffusion and standardised learning outcomes worldwide are offered by the latest OECD/PISA report (OECD, 2015), which confirms and strengthens the doubts cast by a previous report (OECD, 2011). The 2015 report analyses the relationship between the quantity of students' self-reported ICT use at home and at school and their performance in the PISA test on reading and mathematics. It confirms that the frequent use of tablets and computers in schools is more likely to be associated with lower results. Authors also note that countries with the best-performing education systems have normally been very cautious about using technology in the classrooms. This last report raised the issue of the impact of investments in ICT even more urgently for public opinion and policy-makers. However, these are cross-sectional data that cannot provide information about the causality process involved in this relationship.

The impact of ICT provision on learning outcomes lies in a complex web of relationships between different variables inherent in the school, the students and the environment. A number of studies have shown that there are specific conditions in which ICT provision policies can be effective in bettering the educational process. Following an ample literature review, Voogt et al. (2013) provide a list of such conditions, which include technical, human, and organisational support, ICT-related changes in the curriculum, professional development for teachers, content development and management and private–public partnerships. Existing field studies on the relationship between technology and learning performance have not properly addressed the complexity of these factors, which can considerably exceed the usual socio-demographic control variables and could result in biased estimates.

This article aims to make a contribution to this literature by examining how the increase in the stock of three specific devices in Italian lower secondary schools has impacted on the average

school learning performance over a four-year period and in different socio-economic contexts, with controls in place for unobserved heterogeneity.

3. Methodology

3.1 Data

Our data comes from the merging of student SNV/INVALSI test scores from the final exams of lower secondary schools with information from the "Technology Observatory" of the Italian Ministry for Education.

SNV/INVALSI tests measure students' performance in two subjects: Italian language and mathematics.[4] The Technology Observatory is an annual survey carried out by the Italian Ministry of Education involving all state schools (with the exception of schools located in the autonomous provinces of Aosta, Trento and Bolzano), with the aim of collecting data on the available ICT stock.[5] The questionnaire sent to schools has changed between waves. Therefore, harmonisation of the data collated in various years, and with regard to some variables in particular, has been necessary in order to ensure comparability.

The academic years taken into account in the analysis are 2010-11, 2011-12 and 2013-14[6]. All the data was collected at school level, therefore the dependent variables are the averages of INVALSI scores for each school. The reason for choosing a single school unit as the level for the analysis is their comparability in time, unlike data relating to educational institutions (*istituti scolastici*). Hereafter, for the sake of simplicity, we will use the term 'school' instead of 'school unit'. [7]

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[4] They were introduced for the first time in 2004 in Italian primary and lower secondary schools. Since the 2007-08 school year they have been part of the final assessment in lower secondary schools, first as an experimental test and, since 2009-10, as an official part of the exam. Therefore, the results of the INVALSI test contribute to the final mark Italian students receive at the end of lower secondary school.

[5] The first wave was conducted in 2009-10. It has since then been repeated in 2010-11, 2012-13 and 2013-14.

[6] In the 2012/13 school year no data was collected for the Technology Observatory.

[7] Educational institutions in Italy may comprise more than one school that might have been grouped together in different ways throughout the four years considered. In fact, in almost all cases, the school units are identifiable and therefore comparable over time. In particular, INVALSI developed specific identification codes that follow each school over time, regardless of the educational institution to which it belongs and the official codes with which it is labelled during each school year.

Therefore, our final dataset contains panel data that follow Italian lower secondary schools between 2010 and 2014 and which provide information on both the technological stock possessed by each school and the average results of SNV/INVALSI tests for each year.

The choice to focus on lower secondary schools was dictated by the fact that all 8th grade students take part to the INVALSI tests, unlike other school levels, as only in lower secondary the tests are part of the formal student assessment process. Secondly, schools in this grade constitute a more homogeneous group than upper secondary schools, which in Italy are divided into three different pathways (general, technical and vocational), with considerable differences in average ability level and socio-demographic background (Schizzerotto & Barone, 2006). Furthermore, in lower secondary school the diffusion of ICT thanks to public investment in recent years is higher, especially for what concerns the presence of Interactive Whiteboards. For these reasons, we have considered lower secondary schools a more reliable and interesting context for this kind of analysis.

3.2 Methods

The longitudinal nature of the available data allows us to respond to research questions that cannot be answered with cross-section samples or simple time-series data. The technique chosen to estimate the effect of each school's technology stock on its average learning outcomes is the fixed effects regression model[8], which relates students' performance to the presence of ICT in schools. This method has the advantage of controlling for any latent or not-observed variables that characterise the unit of analysis (schools) and which remain constant over time. In our case, for example, the estimated fixed effects model helps to eliminate distortions caused by the concentration of technology in the 'best schools', those that have the best, younger teaching staff or that are located in the best socio-economic backgrounds. However, changes in these same characteristics that have occurred in a school over the period under analysis (such as the arrival of a better motivated head-teacher, or a sudden rejuvenation of the teaching staff) are not controlled for with this technique (a more detailed discussion of our empirical strategy and our model can be found in appendix A).

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[8] The Hausman test confirmed the choice of using fixed effects regression models rather than a casual effects model. First differences models have also been tested. The Cumby-Huizing autocorrelation test indicates that this technique is only marginally more suited than fixed effect regression. The root-mean-square error is higher in first differences regression compared with fixed effects models.

We then explore two sources of heterogeneity in the correlation between ICT and students' performance interacting our ICT variables with geographical area dummies and quintiles dummies capturing the position of each school in the initial distribution of school performance. To be able to measure the initial relative position of each school, we use the first wave of our data and thus throughout the paper, we use only two waves of the panel dataset[9] in our estimates and exclude the first wave (see Appendix A for further information).

3.3 Dependent variables

The dependent variables used in the analysis are the SNV/INVALSI test scores in Italian language and mathematics corrected for the so-called 'cheating' effect[10]. Each subject was considered separately. We computed the deviation from the annual mean of the INVALSI score for each school: the difference between the mean score in each school and the national average for each year in percentage points: this is equal to 0 if the mean of the school is the same as the national average, becomes negative if it is less than the national average and is positive if the school average is higher than the national average. The use of a de-meaned variable rather than the simple average score allows a better comparison between different school years. The difference in some features characterising the test does not in fact permit a direct comparison between results obtained in different years. Furthermore, in this way we also control for average differences in each cohort of students.

Data from the 2010-11 school year were used as the starting point to determine the initial learning performance of each school and excluded from the regression analysis. Fixed effect models were then run on 2011-12 and 2013-14 data.

To avoid effects led by outliers, we excluded all schools where the score was corrected because of estimated cheating effects of more than 0.9.[11] This meant dropping around 8% of the observations. Then we computed the difference in test scores compared with the previous year and eliminated schools with a variation compared with the previous year falling in the two 10% extremes (positive or negative) of the distribution. The 10% outlier window is usually accepted in literature as part of the trimming of outlier data. This allows schools with a variation in INVALSI scores of up to 42 percentage points in between years to be dropped. The process

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[9] Fixed effect and first difference produce identical estimates for T=2 (Wooldridge 2002, p. 284)

[10] The effect of cheating is measured through a percentage indicator that estimates which part of the observed score could be ascribable to anomalies that could change the results of the test (Falzetti, 2013).

[11] This means that the actual average score of the school was multiplied by a factor lower than 0.9, thus reducing the final score.

was run separately for Italian language and mathematics tests. Therefore, our two operative samples may be slightly different in terms of observations.

We also included in the specification a dummy year for the last year, in order to control for differences in the distribution of test scores in different years, the difference in level already being controlled for by the de-meaning procedure.

3.4 Independent Variables

We use measures on the stock of three different technologies as our independent variables: the share of classes within each school equipped with Interactive Whiteboards (IWBs), the share of classes with a wireless connection and the number of mobile devices available in each school (even if their presence in Italian schools is still limited compared with the total number of students). The number of classrooms equipped with an IWB has increased from 17% in 2010-11 to 31% in 2013-14. The increase has been particularly significant in southern Italy, thanks to the EU funds aimed specifically towards them. Wireless coverage also significantly increased over the same period: from 11% of classrooms with a wireless connection in 2010-11 to over 56% of classrooms connected in 2013-14. Figures about mobile devices are still very low: tablets are not a widespread tool in Italian schools. In 2010-11 they were not present at all, while in 2013-14 over 94% of schools still had fewer than 10 mobile devices. Only 1% of schools were equipped with more than 50 devices. Therefore, in the vast majority of schools there is only one device per class, and it is mainly used by the teacher.

We also added control variables such as the number of pupils in the school (school size), the peripheral status of the school (a dummy variable indicating whether the school is located in municipalities other than that of the school headquarters), the percentage of female pupils, the percentage of foreign students, the proportion of students with non-regular school patterns (repeaters), the total number of classes in the school, the amount of ERDF (European Regional Development Fund) and ESF (European Social Fund) funds received for projects not related to new investments in technology completed in the reference year [12].

4. Results

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[12] For example, the sums referring to projects finished between 1/1/2010 and 31/12/2010 have been allocated to the 2010-11 school year. The choice of the 31/12 cut-off was driven by the assumption that the effects of many purchases or projects are not always immediate, and therefore those ending close to the final tests might not yet have had an impact on pupils' performances.

The impact of the increase in technology equipment on Italian language and mathematics performance, as measured by INVALSI test scores, has been analysed separately for each technology considered. The results of the fixed effects regressions for the two models on the presence of technology in lower secondary schools for the whole national territory can be observed in Table I.

Overall, it appears that investments in new technology did not bring about the expected results in terms of standardised learning performance, which is usually considered their first indicator of success (see introduction). Indeed, the increase in IWB equipment is not associated with any statistically significant increase in schools' average relative INVALSI performance, either in mathematics or in Italian language (columns I and II of Table I): schools that have increased their technology equipment more than others did not experience an improvement in their average performance compared with the national average. The same result emerges when we consider the increase in wireless connections in classrooms (columns III and IV in Table I). These results are all the more relevant considering the increase in both technologies in the period under examination described in the previous paragraph. As expected, the number of mobile devices also did not exercise a significant influence on either Italian or mathematics test scores (columns V and VI, Table I).

Table I about here

Such a lack of effects of technology on student learning could be due to the fact that we are using national data, which conceal different impacts in different areas of the country with different socio-economic backgrounds. The north and south of Italy are very different in terms of their socio-economic conditions. The centre ranks in the middle of these two extremes. In 2013, the Institute of National Statistics estimated that average per capita GDP stood at 33.5 million euro in the north-west of Italy and 31.4 million euro in the north-east. It was 29.4 million euro in central Italy, and just 17.2 million euro in the south. This statistic shows the huge economic gap between northern and southern Italy. Learning achievements are also polarised between the north and south of the country, according to INVALSI and OECD/PISA (Gasperoni, 2011), with the centre in a middle position. To give an example, in the PISA 2012 survey Italian students' learning performance in mathematics was 485 (below the OECD average of 500). However, the north-east part of Italy shows an average score of 514, the north-

west 504, the centre 485, the south 464 (excluding the islands) and the southern islands (Sicily and Sardinia) 446. These differences have remained relatively stable since PISA surveys first began, in 2000 (INVALSI, 2012).

Table II shows interactions between technological variables and a set of dummies for these three areas. As expected, some differences in the impact of IWB provisions emerge (Columns I and II in Table II). In mathematics, a positive and significant effect emerges in the north, while it becomes non-significant in the centre and significantly negative in the south. No significant coefficients emerge on performances in Italian language. As far as learning in mathematics is concerned, the table shows that the lack of significance found for the Italian territory as a whole actually conceals two opposing and significant effects: positive in the north and negative in the south. The same pattern emerges when we consider the percentage of classrooms equipped with a wireless connection. No effects are found on Italian language tests (columns II and IV). Finally, the case of mobile devices fully confirms these findings (column V and VI).

Table II about here

If the statistically significant effects found in mathematics are clearly at opposite extremes in the north and the south of Italy, what about their substantial relevance? Let us consider the effect of the percentage of classrooms equipped with an IWB in northern Italy on mathematics performance (0.025). A 1% growth in the number of classrooms with IWBs increases the distance above the national average INVALSI score by 0.025. This means that a school with no interactive whiteboards in 2011 that purchased an IWB for each of its classrooms (reaching a coverage of 100%) experienced an average improvement on the national average of 2.5 points (i.e. if it was 10 points below the average in 2011, it would be 7.5 below it in 2014). Similarly, in the south, equipping all classrooms with an IWB causes an average decrease of 2.3 points in relative performance in mathematics. This increase roughly represents half of the standard deviation of the dependent variable[13].

In the literature, there is evidence that the impact of technology in schools is more likely to emerge among students with lower performances (Checchi et al., 2015), also specifically with respect to Interactive Whiteboards (Higgins et al., 2005). In fact, the lack of significant effects on the average could conceal different and contrasting effects along the distribution of

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13 The standard deviation is 5.598164 for Mathematics and 4.896112 for Italian.

performances. If this applies to students, we could expect it to be true at the school level as well. In an overall analysis, we do not find a consistent differential effect along the distribution of schools, contrary to this literature.[14] However, it is possible that within specific areas different effect sizes emerge along the initial distribution of school performance. As Tables III, IV and V show, the geographical polarisation that emerged in the previous analysis in mathematics performance is mainly driven by low- and middle-attaining schools in the north which clearly benefited from technology (IWBs in particular), while negativity in the south is mainly driven by high-attaining schools.

Table III about here
Table IV about here
Table V about here

Even if there are some differences, this trend emerges for all three technologies in mathematics performance. Conversely, no clear trends appear for the effect of IWBs on Italian language performance, with the exception of the presence of wireless connections which seem to impact positively on the worst quintiles in all geographical areas.

The very high coefficients emerging in the centre as an effect of the increase of the number of mobile devices require discussion, as do all the other results in Table V. As this technology was still common in a very limited number of schools during the years considered and can be used either by teachers and by students (but we do not have information to identify who is using it), these results remain difficult to interpret.

6. Discussion and Conclusions

In this paper we provide a detailed and robust estimation of the impact of different types of digital technology on learning performances in Italian lower secondary schools over a four-year period. For the first time in this field of research, we are able to estimate the effect of the increase in schools' stock of three specific technologies (IWBs, Wi-Fi connection and mobile

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[14] A possible reason for this is that existing studies were not able to control for school or student fixed effects, and used value-added models as an identification strategy. Our own data, if analysed with simple value-added models, show positive and significant effects in the first quintiles and negative effects in the last ones, according to this literature. These analyses are available upon request to the authors.

devices) on learning outcomes in mathematics and Italian language, controlling for fixed effects.

The results show that at a national level no significant impact emerges for any of the three technologies considered. These results challenge the - often implicit - assumption that the provision of ICT exerts an important influence on school learning levels. Also, our detailed data and more robust estimation technique can contribute to the consolidation of such general finding in this field of literature.

However, the second part of our study adds relevant details that show how this general finding conceals different impacts in the different sub-groups of our sample. Indeed, an analysis by geographical areas shows that – as far as mathematics is concerned – schools in northern Italy seem to benefit from the increase of their technology stock, no significant results emerge in the centre, and even a negative effect is visible in the south of Italy. In this way, in poorer areas of the country, technology seem to be not only irrelevant but even detrimental to learning outcomes. Then, by analysing how the effects in these geographical areas change along the initial performance distribution of schools, we show even more complex patterns of differentiation: the positive effect found in the northern part of the country is driven by schools that initially show lowest to medium performance levels. Conversely, in southern schools with the best initial performance, technology has a detrimental effect and these schools drive the negative results found in this area. These more detailed results are of great significance, because they clarify that policies aiming to introduce digital technology in schools have both positive and negative potential, and that the deployment of this potential strongly depends on contextual factors.

How should we interpret this evidence? The positive effects found in the north suggest that, at least in some parts of the country, the results expected by policymakers have indeed manifested themselves. It is, however, more difficult to interpret the negative effects emerging in the south. One can argue that ICT can be ineffective, but it becomes challenging having to explain why ICT can actually be detrimental. Since we use fixed effects models, we are controlling for differences that are stable throughout the period. The determinants of the north-south gap are therefore to be sought primarily in the different temporal evolution of the ability to react to technological provision in the various areas of the country. The most reasonable hypothesis is therefore that in the two areas the ability to capitalise on the arrival of new technology has developed differently. One could borrow from the concept of technological innovation 'absorptive capacity' developed in economics. This concept defines a company's ability to recognise the value of innovation, assimilate it and apply it to specific ends (Cohen and

Levinthal, 1989). In southern Italy, the capacity to absorb new technology could have developed at a slower pace throughout the period considered: without proper development of this capacity, the effect of digital technology effect might not be noted or might even be counterproductive if the innovations interfere with existing organisational balances. It should also be noted that these results concern lower secondary schools, where there is no technical personnel providing support to teachers in the management and maintenance of technology equipment. This fact may have caused greater organisational difficulties, especially where the introduction of technology was on a more massive scale and at a faster rate, as in the four "convergence regions". The sudden and non-selective arrival of new technology, coupled with management issues deriving from the lack of internal expertise for management of the tools acquired, may have caused more organisational problems in these regions. Finally, in the case of northern Italy, reverse causality cannot be excluded: schools going through a process of ongoing improvement (that is beyond the control of the fixed effects regression technique) may have attracted more technology than others and have experienced an improvement in performance, regardless of ICT. This type of school may have driven the trend. The data available do not, however, allow us to make a thorough examination of these possible interpretations, and we have to leave this puzzle to further research with different datasets.[15]

The second results that need to be discussed carefully relate to the emergence of benefits in average and lowest-performing schools in the North and a contrasting detrimental effect in high-performing schools in the south. Past literature at student level shows that the positive effects of technology provision are concentrated among the lowest-achieving students (Higgins et al., 2005, Checchi et al., 2015). This result is usually interpreted to mean that technology serves as a motivational push in environments that are in need of new attention-attracting stimuli for students. On the contrary, new opportunities could interfere with existing well-functioning teaching mechanisms. In a qualitative analysis of 48 schools in southern Italy, Giusti et al. (2015) show that ICT is adopted and used with more enthusiasm in less well-equipped contexts, while schools already performing well are more cautious about them. However, while simple technology provision is more likely to benefit lowest-performing more

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[15] We should also consider the different process leading a school to acquire new technology which is often very different for northern and central Italy compared with what happens in the south of the country (and especially in the four 'Convergence Regions'). In northern and central regions the most well-equipped schools are those willingly participating in government projects (e.g. Cl@ssi 2.0), or schools that have put in place special public-private collaboration projects. In the south, and especially in the four convergence regions, massive and widespread provision of ICT has been guaranteed by European funds in the past 15 years. This may have led to greater motivation in ICT use in northern schools, which were able to introduce technology despite the reduced availability of public grants. However, the difference between the north and the centre shows that this conclusion is not sufficient to interpret our results satisfactorily.

than best-performing schools, in our data this effect is only visible in the highest socio-economic areas. Probably the effect needs contextual conditions to manifest that are not present in the south, and only partially in the centre. In contrast, well-performing southern Italian schools could have experienced the massive arrival of technology as an additional burden rather than as an opportunity.

Finally, we also need to tackle the question of why benefits and detriments are concentrated in mathematics while Italian language seems to be less influenced by the technological stock at the school's disposal. This is in accordance with findings by Comi et al. (2016) and Pagani et al. (2015), while contrasting with what Checchi et al. (2015) found. A possible reason for this could lie in the different use of ICT in the two subjects. In a national evaluation survey on the use of ICT in southern Italian schools (Giusti et al., 2015) it emerged that teachers mostly exploit the most basic functions of IWBs and wireless connections, using them as a blackboard replacements, or to project slides and video.

However, there is also a minority using didactic software. In particular, free maths software called "GeoGebra" has had massive diffusion in Italian middle schools. In fact, maths teachers use didactic software at least once a week more frequently than Italian language teachers (38.7% vs. 31.3%). Italian language teachers are also more likely to be ideologically resistant to technological innovation. We can speculate that maths teachers have used IWBs slightly more than Italian language teachers and, specifically, that they have had more specially designed software with specific learning goals at their disposal. In the absence of such specific software and in humanistic subjects in particular, the use of IWBs is probably left more to teachers' own design of texts. Drawing on illustrative examples of technology use in secondary UK schools, Jewitt et al. (2007) show that questions can be raised about the relationship between the fast pace often observed in lessons with IWBs and effective learning. Indeed the use of fast slide presentations may result in a rigid framing and poor interactivity, especially in English teaching.

However, the lack of effects on Italian language teaching includes a significant exception: the percentage of classrooms with a wi-fi connection shows a positive effect in low-achieving schools, in all the three areas of the country. How can we explain this result? The first and simplest opportunity for a teacher equipped with a wireless connection in the classroom is the possibility of searching for information online. Online information searches during lessons is the most frequent activity using connectivity technology in southern Italian schools (Giusti et al., 2015). There is also evidence that such forms of collaborative use between teachers and students have positive impacts on learning achievements, especially as regards the Italian

language (Comi et al., 2016). Therefore, we can interpret the positive and significant coefficient emerging regarding Italian language in the lowest quintiles in all geographical areas as the positive impact of the possibility of searching online together in the classrooms. Probably this opportunity is easily available in any context once a connection is present and is less in need of organizational support than the use of IWBs or tablets.

Finally, this study has a number of limitations that need to be carefully considered. First, it is clear that the role of the teacher and his or her unobservable characteristics (such as the ability to motivate, digital skills and beliefs in ICT) are crucial in ensuring the successful introduction of ICT (OECD, 2001). Different development of teachers' skills in exploiting technology in the various areas in the period considered could also lie behind our results. Future research will have to analyse how these teaching styles interact with technology use in the enhancement of learning outcomes. Second, the results presented here only concern lower secondary schools and a limited period of time: it is possible that the relationships studied here would be different in other school years and periods of time. These results also regard a relatively initial phase in the diffusion of ICT in schools, especially in southern Italy. It is possible that our results are finding temporary effects that could change direction and strength as technology becomes a standard tool in schools. Lewin et al. (2008) found a positive relationship between benefits from IWB use and the length of time pupils had been taught with this tool. Furthermore, it is important to be aware that in this study we have used only two indicators of learning, although these are the most important and widely used in learning performance measurement literature. The impact of ICT provision on so-called 21st-century skills risks remaining undisclosed. We do not know whether the purchase of technological equipment has had a positive effect on students' digital skills, for example. In fact, an urgent need for alternative assessment approaches and instruments is identified by many scholars, especially if aimed at measuring 'digital literacy' or 'digital skills' (Anderson, 2008; Voogt et al., 2013) but also by institutional reports (Avvisati et al., 2013). We already have clues that these kinds of skills could benefit from the introduction of technological equipment in schools (Giusti et al. 2015), and that higher digital skills improve learning performance in high schools (Pagani et al., 2015). However, we lack solid, large-scale data to test this hypothesis.

Future research will have to deliver better evidence on the greater benefits that technology seem to have on lowest performing schools. Also, it will need to analyse which of the differences between Italian geographical areas are mostly responsible for their different capacity to benefit from technology and check whether this pattern also exists in other countries. Considering the large provision of publicly funded ICT in the south, the role of the massive distribution of

technology in mediating the impact of digital technology on learning will also need to be analysed.

Acknowledgements

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Appendix A: methodology.

The longitudinal nature of the available data allows us to respond to research questions that cannot be answered with cross-section samples or simple time-series data. Our data allow us to use a fixed effect model of the following form[16]:

$$Y_{st} = \alpha + \beta_1 \times ICT_{st} + \tau_t + \mu_s + \theta X_{st} + \varepsilon_{st} \qquad\qquad (A1)$$

where "*st*" denotes the *s*-th school at time *t*. *Y* is a measure of student performance, *ICT_{st}* is a measure of the school stock of ICT technologies at time t, τ_t and μ_s are, respectively, time and school fixed effects, *X* is a vector of time-varying schools' characteristics and ε is the error term. This method has the advantage of controlling for any latent or not-observed variables that characterise the unit of analysis (schools) and which remain constant over time. In our case, for example, the estimated fixed effects model helps to eliminate distortions caused by the concentration of technology in the 'best schools', those that have the best, younger teaching staff or that are located in the best socio-economic backgrounds. However, changes in these same characteristics that have occurred in a school over the period under analysis (such as the arrival of a better motivated head-teacher, or a sudden rejuvenation of the teaching staff) are not controlled for with this technique. Thus, we cannot interpret our results as the causal effects of ICT on students' performance but we are clearly taking into account time-constant heterogeneity and ruling out a source of self-selection of schools into ICT investment. Unfortunately, our results still suffer from selection bias due to time varying characteristics, which exists if cov(ICT_{st}, ε_{st}) is different from zero. Finally, year fixed-effects control for any change overcoming all schools in any given year. In this specification, the parameter of interested is β1.

We then explore two sources of heterogeneity in the correlation between ICT and students' performance interacting our ICT variables with geographical area dummies and quintiles dummies capturing the position of each school in the initial distribution of school performance. Of course, the relationship between those sets of dummies and students performance could not be identified in a fixed effect model because they are time-invariant, but the interaction term is

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[16] The Hausman test confirmed the choice of using fixed effects regression models rather than a casual effects model. First differences models have also been tested. The Cumby-Huizing autocorrelation test indicates that this technique is only marginally more suited than fixed effect regression. The root-mean-square error is higher in first differences regression compared with fixed effects models.

perfectly identified and will show us how ICT affect students' performance in each area and in each quintile. To be able to asses the relative position of each school in the initial distribution, we use the first wave of our data to rank schools with respect to students performance, divide the distribution in quintiles and then interact the set of quintiles dummies with our ICT variables in equation A1. Thus, throughout the paper, we use only two waves of the panel dataset[17] in our estimates and exclude the first wave.

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[17] Fixed effect and first difference produce identical estimates for T=2 (Wooldridge 2002, p. 284)

TABLES

Table I - Effect of the increase in the percentage of classes with an IWB, the percentage of classes with a wireless connection and the number of mobile devices in Italian lower secondary schools in the 2011-2014 period.

	Maths	Italian	Maths	Italian	Maths	Italian
VARIABLES						
% of classes with a IWB	0.002	-0.003				
	[0.005]	[0.003]				
% of classes with wireless connection	-	-	-0.002	0.000		
			[0.002]	[0.002]		
Number of mobile devices					-0.004	0.005
					[0.007]	[0.005]
Observations	7,789	7,912	7,883	8,016	7,908	8,047
R-squared	0.071	0.030	0.070	0.029	0.069	0.029

Note: Standard errors in square brackets are clustered at regional level.
*** p<0.01, ** p<0.05, * p<0.1

Table II – Effect of percentage of classrooms equipped with IWBs, wireless connections and mobile devices among Italian lower secondary schools in the 2011-2014 period, in different geographical areas

VARIABLES	Maths	Italian	Maths	Italian	Maths	Italian
% of IWBs * North	0.025***	-0.004				
	[0.007]	[0.003]				
% of IWBs * Center	-0.011	-0.005				
	[0.009]	[0.004]				
% IWBs * South	-0.023***	-0.000				
	[0.007]	[0.006]				
Wireless coverage * North			0.007***	-0.001		
			[0.003]	[0.002]		
Wireless coverage * Center			-0.004	-0.000		
			[0.005]	[0.003]		
Wireless coverage * South			-0.020***	0.003		
			[0.005]	[0.003]		
Mobile devices * North					0.052***	0.009
					[0.015]	[0.009]
Mobile devices * Center					-0.018	-0.005
					[0.007]	[0.004]
Mobile devices * South					-0.047**	0.012
					[0.012]	[0.008]
Observations	6,842	7,912	7,883	8,016	6,943	8,047
R-squared	0.084	0.030	0.088	0.030	0.073	0.029

Note: Standard errors in square brackets are clustered at regional level.
*** p<0.01, ** p<0.05, * p<0.1

Table III – Effect of percentage of classrooms equipped with an IWBs among Italian lower secondary schools in the 2011-2014 period, in different geographical areas and by performance quintile (2010-11)

	Maths			Italian		
	North	Center	South	North	Center	South
quintile 1	0.027*	0.012	-0.005	0.016	-0.003	0.004
quintile 2	0.021**	-0.032	-0.023	0.003	0.017***	-0.020**
quintile 3	0.033***	0.016	-0.034	-0.015***	-0.007	0.012
quintile 4	0.017	-0.008	-0.066**	-0.020***	-0.013	0.010
quintile 5	0.021*	-0.045*	-0.066**	0.006	-0.025***	0.003

Table IV – Effect of percentage of classrooms equipped with a wireless connection among italian lower secondary schools in the 2011-2014 period, in different geographical areas and by performance quintile (2010-11)

	Maths			Italian		
	North	Center	South	North	Center	South
quintile 1	0.000	-0.011*	-0.003	0.018***	0.012*	0.006**
quintile 2	0.012**	0.005	-0.016*	-0.004	0.003	-0.006
quintile 3	0.011**	0.009	-0.024**	-0.002	-0.006	-0.003
quintile 4	0.013***	-0.005	-0.035***	-0.007***	0.002	0.009
quintile 5	-0.006	-0.022***	-0.068**	0.003	0.004	0.004

Table V – Effect of the number of mobile devices among Italian lower secondary schools in the 2011-2014 period, in different geographical areas and by performance quintile (2010-11)

	Maths			Italian		
	North	Center	South	North	Center	South
quintile 1	0.125	0.263***	-0.062	0.094***	-0.006	0.043
quintile 2	0.090***	-0.038	-0.072	-0.035**	-0.068***	0.060
quintile 3	0.008	-0.025***	-0.159***	-0.021	-0.004	-0.005
quintile 4	0.092**	-0.007	-0.202	0.015	-0.029	-0.045
quintile 5	-0.023	-0.022	-0.067**	0.025	0.015	0.004